

# Examining the role of biomass energy for sustainable environment in African countries

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## Research Article

**Keywords:** CO2 emissions, Biomass, Fossil fuel, trade openness, GDP per capita, Africa

**Posted Date:** August 4th, 2022

**DOI:** <https://doi.org/10.21203/rs.3.rs-1723447/v1>

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24 **ABSTRACT**

25 **Purpose-**This paper investigates the influences of biomass energy use, fossil fuel, income, trade  
26 openness, and population growth on carbon dioxide (CO<sub>2</sub>) emission in African countries over the  
27 1980-2014 period.

28 **Design/methodology/approach-** The study employs pool mean group (PMG), mean group (MG),  
29 and dynamic fixed effect (DFE) estimators that resolve the issue of heterogeneity bias. In addition, it  
30 employs weighted fully modified ordinary least squares, and weighted dynamic ordinary least  
31 squares to validate the robustness of PMG, MG, and DFE estimates.

32 **Findings-** The results from each of these estimators complement one another and both suggest that  
33 the relation of fossil fuel use and population growth with CO<sub>2</sub> emission is positively significant.  
34 Conversely, we find that trade openness and biomass energy use exert significant negative impact on  
35 carbon emission. Additionally, the dampening effect of biomass energy utilization on CO<sub>2</sub> emission  
36 helps to validate Environmental Kuznets Curve (EKC) hypothesis for those countries.

37 **Originality/value-** The role of biomass in determining environmental quality has been investigated  
38 by studies for a few developed economies and developing countries without reaching consensus in  
39 terms of their findings. As indicated by the literature, such study is wanting in African countries, and

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40 this motivates the present study. More so, with focus on the role of biomass in CO<sub>2</sub> emission, this  
41 study first considers sixteen countries from all the regions on the African continent. The findings of  
42 this study will assist policy makers in making useful environmental and sustainable energy policy  
43 that can be embraced as regional policy.

44  
45 *Keywords:* CO<sub>2</sub> emissions, Biomass, Fossil fuel, trade openness, GDP per capita, Africa  
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## 47 1. Introduction

48 The challenges of global warming and rampant climate change have continued to attract the  
49 attentions of policy making authorities, environmentalists, and society at large. More attention is  
50 needed as the global energy use and carbon dioxide (CO<sub>2</sub>) emissions rose simultaneously by 2.9%  
51 and 2.0% respectively in recent time, exceeding their growth rates recorded each year since 2010 to  
52 2011 (BP, 2019). Carbon emissions through increase in greenhouse (GH) gases, causes the global  
53 temperature to rise, earth's surface to warm, and as a result changes the climate. Consequently, there  
54 would be drought, low agricultural yield (Yahaya et al., 2020), poor state of human health and  
55 people's well-being (Danish and Wang, 2019; Adeel-Farooq et al., 2021). Limiting warming to an  
56 estimate of about 1.5°C above pre-industrial levels would be desirable and require universal  
57 implementation of cross-sectoral climate mitigation, combined with sustainable development (IPCC,  
58 2018). Therefore, understanding the causes of global warming and solutions to its challenges will be  
59 helpful to transition to a low carbon, and toward attaining the Sustainable Development Goals  
60 (SDG).

61 As earlier shown in the literature, one of the major causative factors of gaseous emissions is  
62 economic growth (Beckerman, 1992; Grossman and Krueger, 1991, 1995; Shafik, 1994). Due to its  
63 substantial, contribution to the gaseous emissions, economic growth is often used to test the  
64 Environmental Kuznets Curve (EKC) hypothesis by examining its relationship with environmental  
65 pollution. The hypothesis connotes that a threshold exists for a worsening environment as the level of  
66 per capita income continues to increase. This threshold is attained when the average income gets to a  
67 particular level and shows an inverted U-shaped relation with environmental degradation. The path-  
68 breaking empirical study on EKC was credited to Grossman and Krueger (1995) who found an U-

69 shaped EKC, by using a quadratic EKC in levels. Subsequently, some earlier studies such as  
70 Beckerman (1992), Shafik and Bandyopadhyay (1992), Panayotou (1993), and Shafik, (1994) have  
71 also found an inverted U-shaped EKC, which suggested a non-linear relation of per capita income  
72 with pollution. However, studies such as Selden and Song (1994), Stern et al. (1996), and Saboori et  
73 al. (2012) failed to validate EKC hypothesis, though concluded that economic growth hurt the quality  
74 of environment. Due to lack of unanimous conclusion on the outcomes of EKC, the hypothesis  
75 continues to receive researchers' attention till today.

76 In addition, the use of energy generated from fossil fuels has played a vital role in GHGs  
77 emissions (Bilgili, 2012; Katircioglu, 2015; Yahaya, et al., 2020). Global warming and climate  
78 change according to IPCC are results of CO<sub>2</sub> emissions from the fossil fuels burnt. Effort to avert the  
79 impacts across ecosystems and economies requires that global warming be stabilized at 1.5°C by  
80 cutting fossil fuel use (IPCC, 2018). The priority to achieve this goal has motivated the pursuit of  
81 alternative energy sources and environmental sharp restraints on fossil fuel energy use, compelling  
82 industries to consider renewable fuels. The use of energy from its clean source is viewed an effective  
83 tool of solving the current environmental problems (Owusu and Asumadu-Sarkodie, 2016), and the  
84 use of such clean energy has been increasing in recent time (Danish and Ulucak 2020). Biomass as  
85 source of renewable energy (known as bioenergy) has the potential of easing the concerns of GH  
86 gases emissions and global climate warming and could serve as substitute to the fossil fuel, a non-  
87 renewable energy source. As noted by Shahbaz et al. (2021), the substitute energy sources should be  
88 recognized as a policy tool to make energy clean and cost-effective and thus, as a tool to ascertain  
89 energy security.

90 Biomass constitutes wood made from forest and agro-industrial plantations, or non-wood  
91 generated from plant stems, leaves, crop remains, etc (Bildirici & Ozaksoy, 2018; Schuck, 2006). In  
92 its various forms, biomass has been used for production of fuel, heat and electricity generation,  
93 Further; biomass wood has been used directly for cooking purpose too. Conventionally, the use of

94 biomass energy is based on the belief that carbon emissions from the burning of biomass have  
95 neutral or zero global warming effects (Liu et al., 2020) as such emissions are considered being  
96 offset in the process of plants' photosynthesis (Darda et al., 2019). Hence, bioenergy sourced from  
97 biomass may help to resolve GH effect by curbing carbon emissions efficiently.

98 Incidentally, most developing nations employ biomass energy to satisfy around 35 percent of their  
99 domestic energy needs (Sarkodie et al., 2019). In this context, African countries are not left out. For  
100 example, the countries are very rich in biomass and a sizeable percentage of Africans generates more  
101 than 80% of fuel from biomass to meet their cooking needs (UNDP, 2009). Besides, African  
102 household who makes up the low-income bracket obtains around 80 to 90 percent of their needed  
103 energy from biomass source (Iiyama et al., 2014). The use of this type of energy is likely to influence  
104 the level of gaseous emission in those countries.

105 A possible question is, can biomass energy use enhance environmental quality by lessening CO<sub>2</sub>  
106 emissions? A survey of literature suggests that the question has been answered for a few developed  
107 economies (see Baležentis et al., 2019; Bilgili, 2012; Bilgili et al., 2016; Bilgili et al., 2017; Sarkodie  
108 et al., 2019; Shahbaz et al., 2017) and developing countries (see Adewuyi and Awodumi 2017;  
109 Carvalho et al., 2019; Danish and Ulucak, 2020; Katircioglu, 2015; Shahbaz et al., 2019; Wang et  
110 al., 2020). These studies found that biomass energy helped to mitigate pollution. However, Shahbaz  
111 et al. (2018) for developed economies and Adewuyi and Awodumi 2017, Solarin et al. (2018) and  
112 Mahmood et al. (2019) for some developing countries found that biomass energy use degraded the  
113 quality of environment. As observed by Adewuyi and Awodumi (2017), and Danish and Wang  
114 (2019), little is known in the literature concerning the relation of biomass energy use with pollution,  
115 as no consensus is reached by those few studies in terms of their findings. Thus, there is need for  
116 more studies to deeply understand how biomass energy impacts carbon emission. More importantly,  
117 the literature indicates that such study is indispensable in the context of African countries.

118 As noted earlier, African countries are endowed with biomass and a large percentage of Africans  
119 generates fuel from biomass to meet their energy requirements. Unfortunately, not much attention is  
120 dedicated to the role of biomass in carbon emission in African countries. Considering this, our study  
121 examines the role of biomass in CO<sub>2</sub> emission in sixteen African countries from all the African  
122 regions, namely Northern, Western, Eastern, Southern, and Central Africa. This enables to  
123 understand the importance of biomass resources across the regions on the African continent, which  
124 will assist policy makers in making useful environmental and sustainable energy policy that can be  
125 embraced as regional policy.

126 Furthermore, studies with biomass focus are very few and some of these studies have neglected  
127 the role of vital variables such as trade openness and population growth in carbon emission. Given its  
128 technique, scale, and composition effects, trade openness plays a crucial contributing role to  
129 emissions (Farhani et al., 2014) and its inclusion in a carbon emission model will be useful. In  
130 addition, Fan et al. (2006) argue that the role of population growth in determining the quality of  
131 environment cannot be neglected while modelling environmental impacts. Hence, our study  
132 investigates carbon emission and biomass nexus by including trade openness and population growth  
133 in the model. The result of including these variables will be helpful to African policy makers in  
134 considering their role to address pollution while striving to attain sustainable development.

135 In terms of methodological approaches, this study considers the cross-sectional dependence (CSD,  
136 henceforth) issue unlike earlier studies. It is observed that failure to consider CSD may flaw studies,  
137 as results may be inconsistent, if the cross-sectional units are correlated. Therefore, we account for  
138 this issue and employ various second-generation panel estimation methods, such as Pesaran CADF  
139 and CIPS tests for unit roots, and Westerlund bootstrap ECM panel cointegration tests, which are  
140 robust to CSD. For the parameter estimates, we first apply mean group (MG), and pool MG (PMG)  
141 estimators that provide solutions to the issue of heterogeneity bias. Then, we employ second-  
142 generation estimators such as weighted FMOLS, and weighted DOLS, which deal with potential

143 autocorrelation and endogeneity problems, to validate the results obtained from PMG and MG  
144 estimators. Our findings from those estimators complement one another. Hence, they are reliable,  
145 robust, and free of inconsistencies.

## 146 **2. Literature review**

147 Recently, the necessity to minimize climate change resulting from CO<sub>2</sub> emissions has made clean  
148 energy to receive an increasing attention on strategies for sustainable resource exploitation. The  
149 motivation for the increasing attention is not unconnected with the conclusion of some studies (as  
150 reviewed below) that the exploitation of biomass energy helps to dampen CO<sub>2</sub> emissions. In this  
151 paper, to conserve space, we decided to only review related studies that examined the impact of  
152 biomass energy usage, among other determinants, on carbon emissions. Furthermore, we review  
153 studies that investigated whether EKC proposition was valid for a country or panel of countries with a  
154 biomass focus. Finally, we review the previous results of causality among variables including  
155 biomass usage.

156 A survey of literature shows that a few studies included biomass energy use as other determinant  
157 of GH gas emissions and found that biomass energy helped to mitigate pollution of environment.  
158 These studies included Bilgili (2012), Bilgili et al. (2016), and Bilgili et al. (2017) for United States,  
159 Katircioglu (2015) for Turkey, Adewuyi and Awodumi (2017) for Burkina Faso, Gambia, and Mali,  
160 Sarkodie et al. (2019) for Australia, Carvalho et al. (2019) for Western Kenya, Danish and Ulucak  
161 (2020) for China, and Wang et al. (2020) for British Columbia. The findings of these studies indicate  
162 that policy makers efficiently adhere to biomass resource exploitation that society can keep at a  
163 steady level without hurting environment. However, Adewuyi and Awodumi (2017) found that  
164 biomass energy use degraded the quality of environment in other West African countries such as  
165 Nigeria, Senegal, Niger, and Togo.

166 With regards to EKC, some studies tested the validity of the hypothesis with a biomass focus and  
167 found that biomass energy usage helped to achieve inverted U-shaped relation of income with CO<sub>2</sub>

168 emissions. For example, Dogan and Inglesi-Lotz (2017) use the EKC model to examine the influence  
169 of biomass energy usage on CO<sub>2</sub> emission for 22 biomass consuming countries. Findings suggest  
170 that biomass energy usage reduces environmental pollution and EKC holds for the countries. Similar  
171 conclusions were reached by studies such as Baležentis et al. (2019) for the EU countries, Shahbaz et  
172 al. (2017) for United States, Shahbaz et al. (2019) for MENA region and Middle East, and Danish  
173 and Wang (2019) for BRICS economies. The findings of these studies suggest that biomass energy  
174 decreases pollution and corroborates EKC proposition. However, studies such as Shahbaz et al.  
175 (2018) for G 7 countries, Solarin et al. (2018) for 80 countries, and Mahmood et al. (2019) for  
176 Pakistan do not find the relation of biomass energy use with CO<sub>2</sub> emission to be negatively  
177 significant. Concerning EKC, the findings of Shahbaz et al. (2018) and Solarin et al. (2018) support  
178 the proposition whereas those of Mahmood et al. (2019) do not support it.

179 In terms of causality tests, some studies specifically focus on biomass and economic growth to see  
180 the direction of causality between them. For instance, in the studies of US by Payne (2011) and  
181 Aslan (2016), biomass energy is found to Granger-cause economic growth without a feedback.  
182 Similar result confirming the growth hypothesis is found for Latin America by Bildirici (2013), G 7  
183 economies by Bilgili and Ozturk (2015) and 51 countries of Sub-Sahara Africa by Ozturk and Bilgili  
184 (2015). However, Bildirici (2014) finds that biomass energy and GDP Granger-cause each other,  
185 thereby confirming a feedback hypothesis for the transition countries. Studies such as Bildirici and  
186 Ozaksoy (2013) and Bildirici (2013) report that the directions of causality between the variables are  
187 mixed for some EU countries and 10 emerging economies, respectively.

188 Recently, the focus of studies shifts to test the possibility of causalities among CO<sub>2</sub> emission,  
189 GDP, and biomass energy. For instance, Bilgili et al. (2017) and Shahbaz et al. (2017) perform the  
190 causality tests for United States and find that biomass energy and CO<sub>2</sub> emission Granger-cause each  
191 other, thereby confirming a feedback hypothesis. Similar result is found by Shahbaz et al. (2019) for  
192 MENA region and Middle East, and Mahmood et al. (2019) for Pakistan's study. Furthermore, some

193 of these studies (Bilgili et al., 2017; Mahmood et al., 2019; Shahbaz et al. 2017) confirm a feedback  
194 hypothesis between biomass and GDP. With regards to causality between GDP and CO<sub>2</sub> emission,  
195 Shahbaz et al. (2017) report that GDP has a unidirectional causality with CO<sub>2</sub> emission, whereas  
196 Shahbaz et al. (2019) find that the direction is either way.

197 Clearly, the literature shows that researchers are yet to reach an agreement on whether biomass  
198 energy improves or worsens CO<sub>2</sub> emissions. More so, the directions of causal link among CO<sub>2</sub>  
199 emission, GDP, and biomass energy remain ambiguous. All in all, the relation of biomass  
200 exploitation with CO<sub>2</sub> emissions has not been researched extensively unlike its relationship with  
201 GDP. Hence, more research is needed to provide useful and adequate suggestions to policy makers  
202 about biomass energy resource to achieve energy security and usage that can be kept at a steady level  
203 without damaging environment.

### 204 **3. Model, data description, and estimation approaches**

205 This study examines the impacts of fossil fuel, biomass energy use, income, trade, and population  
206 growth on carbon emissions using EKC model in African countries. It follows and augments earlier  
207 studies such as Bilgili (2012) and Katircioglu (2015) who model CO<sub>2</sub> emissions to depend on  
208 biomass energy and fossil fuel use. Specifically, our study augments this previous model by  
209 including GDP per capita and its squared term to further test whether EKC hypothesis exists in  
210 African countries. This leads us to investigate the following model 1.

$$211 \quad \ln C_{it} = \gamma_0 + \gamma_1 \ln B_{it} + \gamma_2 \ln F_{it} + \gamma_3 \ln G_{it} + \gamma_4 \ln Gsq_{it} + e_{it} \quad (1)$$

212 Some studies (Awad 2019; Danish and Wang 2019; Dogan and Seker, 2016; Ha Le et al., 2016;  
213 Ertugrul et al., 2016; Jebli et al., 2016; Managi et al., 2009) indicate that trade openness (TRO) has  
214 potential to predict the change in the level of CO<sub>2</sub> emissions. Hence, model 1 is modified by  
215 including TRO and this yields model 2 as follows:

$$216 \quad \ln C_{it} = \gamma_0 + \gamma_1 \ln B_{it} + \gamma_2 \ln F_{it} + \gamma_3 \ln TRO_{it} + \gamma_4 \ln G_{it} + \gamma_5 \ln Gsq_{it} + e_{it} \quad (2)$$

217 Furthermore, population is considered one of the important influential factors of environmental  
 218 pollution and studies such as Fan et al. 2006, Hashmi and Alam, 2019 and Rauf et al. 2018 include it  
 219 in a model using carbon emission as indicator of pollution. To account for the impact of population  
 220 on CO<sub>2</sub> emissions, therefore, model 3 is specified as follows:

$$221 \quad \ln C_{it} = \gamma_0 + \gamma_1 \ln B_{it} + \gamma_2 \ln F_{it} + \gamma_3 \ln P_{it} + \gamma_4 \ln G_{it} + \gamma_5 \ln Gsq_{it} + e_{it} \quad (3)$$

222 In model (1-3), the measurement of CO<sub>2</sub> emission (lnC) is in metric tons per capita, biomass energy  
 223 use (lnB) in metric tons, fossil fuel use (lnF) in metric tons. GDP per capita (lnG) and its squared  
 224 term (lnGsq) are in constant 2010 US\$, and  $e$  is an error term. In addition, trade openness (lnTRO)  
 225 represents the sum of import and export as a percentage of GDP, and population growth (lnP) is  
 226 measured as the percentage change in the number of people. Natural logarithm (ln) of variables  
 227 enables interpretation of the estimates as elasticities of regressand (carbon emissions) with respect to  
 228 regressors (B, F, TRO, P, G and Gsq). Table 1 further shows the description of the balanced panel  
 229 dataset. Each country in the panel is represented by  $i$  across time  $t$ , and the parameter estimates are  
 230  $\gamma_1$  to  $\gamma_5$ . Based on a priori and the literature, it is expected that the sign of  $\gamma_1 < 0$ , and  $\gamma_2 > 0$ . In  
 231 model 2 and 3, it expected that  $\gamma_3 < 0$  and  $\gamma_4 > 0$ , respectively. The EKC will be satisfied for African  
 232 countries if  $\gamma_4 > 0$ , and  $\gamma_5 < 0$  are achieved with statistical significance.

233 **Table 1: Descriptive statistics**

	lnC	lnB	lnF	lnTRO	lnP	lnG	lnGsq
Minimum	-4.117	15.698	11.264	1.843	-1.831	5.620	31.591
Maximum	2.300	20.144	19.232	4.920	1.487	9.122	83.229
Mean	-0.397	17.551	15.044	4.062	0.765	7.341	54.444
Std. Dev.	1.258	1.005	1.797	0.447	0.513	0.743	11.119
Observations	560	560	560	560	560	560	560

234

235 Concerning the data used, we collected data on carbon dioxide emissions, trade, population  
 236 growth, and GDP per capita from World Bank's world development indicators and got data on  
 237 biomass and fossil fuel energies use from materials flow database (<http://www.materialflows.net>).  
 238 Because current data are not available for some sample countries, the study covers 1980 to 2014  
 239 period and due to limited data, some countries could not be included in the analysis. Despite this  
 240 limitation, the study includes representative countries (Algeria, Egypt, Morocco, Tunisia, Kenya,

241 Mauritius, Zimbabwe, South Africa, Benin, Côte d'Ivoire, Ghana, Nigeria, Senegal, Togo,  
 242 Cameroon, and Democratic republic of Congo) from all the five African regions in the 16 sample  
 243 countries examined.

244 The estimation approach of this study follows steps. It first determines the existence of CSD in  
 245 individual panel dataset using CD-test (Pesaran, 2004). Then, it determines the integration order of  
 246 variables by considering the tests that can resolve the possible issue of CSD in heterogenous panels.  
 247 Hence, it applies the Pesaran (2003) CADF test and Pesaran (2007) CIPS test, which are cross-  
 248 sectionally augmented versions of ADF and IPS unit root tests, respectively. In the existence of CSD,  
 249 both tests are commonly applied to examine unit roots because they can overcome the effect of CSD  
 250 in heterogenous panels. In the case of CADF test, the effect is eliminated by augmenting ADF  
 251 regressions with the cross-section means of the individual variables lagged at levels and first  
 252 differences. The processes applied by the CIPS and CADF tests are similar, but the former employs  
 253 the cross-sectional mean of the latter. In both tests, for the  $H_0$ : all series in a panel have unit roots  
 254 whereas for the  $H_1$ : at least one series has no unit root (i.e., indicating stationarity).

255 If variables are found to be stationary after first differences, the subsequent step is to test for  
 256 cointegration on panel dataset. To accomplish this, we use the Pedroni (1999, 2004), and Kao (1999)  
 257 cointegration tests and Westerlund (2007) bootstrap error correction (EC) cointegration tests. Pedroni  
 258 test yields seven distinct test statistics, which are based on the residuals obtained from the following  
 259 regression, Eq. (4). Four of these test statistics are classified under within dimension and the  
 260 remaining three statistics are under the between dimension with their associated probability values.

$$261 \quad y_{it} = \varphi_i + \alpha_i T + \sum_{j=1}^k \beta_{ji} Z_{ji,t} + \varepsilon_{it} \quad (4)$$

262 In Eq. (4),  $y_{it}$  is the regressand and  $Z_{ji,t}$  are regressors, both of which should be an I(1) for individual  
 263 panel  $i$ . The fixed effects, slope coefficient, and trend are  $\varphi_i$ ,  $\beta_i$ , and  $T$ , respectively. The error term  
 264 is denoted by  $\varepsilon_{it}$  and it is explicitly expressed as  $\varepsilon_{it} = \gamma_i \varepsilon_{it-1} + \vartheta_{it}$ . The residual's autoregressive

266 term is denoted by  $\gamma_i$ . For all the test statistics, the null hypothesis,  $H_0 : \gamma_i = 1$  implies that  $y_{it}$  and  
 267  $Z_{ji,t}$  have no long-run relationship for all  $i$ , and the alternative hypothesis,  $H_1 : \gamma_i < 1$  suggests that  
 268  $y_{it}$  and  $Z_{ji,t}$  are cointegrated for all panels. Also, the study employs panel cointegration test due to  
 269 Kao (1999). The test is based on ADF statistics and does not provide for a time trend unlike Pedroni  
 270 test.

271 For robustness check, we apply Westerlund (2007) bootstrap error correction model panel  
 272 cointegration tests, which resolve the issue of CSD and heterogeneity. The test produces consistent  
 273 and robust results and avoids the issue of common factor restriction. For the cointegrating relation  
 274 between the regressand,  $y_{i,t}$  and regressors,  $Z_{i,t}$ , the error correction (EC) model, Eq (5) is  
 275 estimated.

$$276 \quad \Delta y_{it} = \alpha_i + \varphi_{0i}(y_{i,t-1} - \beta_i Z_{i,t-1}) + \sum_{j=1}^{q_i} \varphi_{1ij} \Delta y_{i,t-j} + \sum_{j=0}^{q_i} \varphi_{2ij} \Delta Z_{i,t-j} + \varepsilon_{it} \quad (5)$$

277 where  $\varphi_{0i}$  measures the speed of adjustment and  $y_{i,t-1} - \beta_i Z_{i,t-1} = 0$  gives the cointegration  
 278 expression. If  $\varphi_{0i} = 1$  it means there is no EC and, therefore,  $y_{i,t}$  and  $Z_{i,t}$  are not cointegrated.  
 279 However,  $\varphi_{0i} < 1$  suggests that EC exists and so  $y_{i,t}$  and  $Z_{i,t}$  are cointegrated. There are four tests  
 280 in total and the outcomes of the test can be classified into two main parts. The first part is the group  
 281 statistics (Gt), which is based on group mean and does not make use of information from the EC. The  
 282 second part is the panel statistics (Pt), which is based on pooled panel knowledge. It pools  
 283 information from cross-sectional EC term. The tests can produce both asymptotic and bootstrap  
 284 critical values. Bootstrapping is particularly essential to address the CSD issue if detected. In this  
 285 test, the  $H_0$  implies that cointegration does not exist for at least one individual panel  $i$  for Gt and for  
 286 all panels for Pt.

287 After establishing the cointegrating relation between variables, next is to compute the  
 288 cointegration estimates. We achieve this by employing panel autoregressive distributed lag (ARDL)  
 289 model. The ARDL method is appropriate for long panel as in the case of this study. The method

290 accommodates variables with mixed integrated order and due to the inclusion of lagged regressand  
 291 and regressors in the model, it can address possible endogeneity problem (Pesaran et al., 1999). A  
 292 specified unrestricted panel ARDL (p, q) model can be expressed as vector error correction model to  
 293 give regression Eq. (6).

$$294 \quad \Delta y_{it} = \varphi_{0i}(y_{i,t-1} - \beta_i Z_{i,t-1}) + \sum_{j=1}^{p-1} \varphi_{1ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \varphi_{2ij} \Delta Z_{i,t-j} + v_i + \varepsilon_{it} \quad (6)$$

295 In Eq. (6),  $y_{i,t-1} - \beta_i Z_{i,t-1} = 0$  is the long-run expression,  $y_i$  is the regressand (carbon emissions),  
 296  $\varphi_{1i}$  are the short-run dynamic estimates of lagged regressands. The lags of regressand and regressors  
 297 are denoted by  $p$  and  $q$ , respectively. The term  $v_i$  denotes fixed effect and  $\varepsilon_{it}$  is the residual term.

298 Eq. (6) can be estimated using pool mean group (PMG), mean group (MG), and dynamic fixed  
 299 effect (DFE) estimators. For PMG estimator (Pesaran *et al.*, 1999), the error correction term ( $\varphi_{0i}$ )  
 300 and parameters of regressors ( $\varphi_{2i}$ ) differ across the panels. However, the long run coefficients ( $\beta_i$ )  
 301 are constant across the panels. The MG estimator (Pesaran and Smith, 1995) estimates the values of  
 302 parameters for each panel in the whole cross-sections and computes the average of these estimated  
 303 values. Both estimates,  $\varphi_{2i}$  and  $\beta_i$  are not restricted and can vary across the panels. For the DFE  
 304 estimator, homogeneity of long-run estimates is imposed while the intercept can vary across  
 305 countries like the PMG estimator. Unlike PMG, however, DFE restricts  $\varphi_{0i}$  and  $\varphi_{2i}$  not to vary  
 306 across the panels. Lastly, Hausman (1978) test determines which of the estimators is more consistent  
 307 and efficient. In other words, it determines whether the long-run estimates are truly homogenous or  
 308 otherwise.

309 In the last step, the study checks to confirm the results obtained from the Panel ARDL estimators.  
 310 To do this, it uses the weighted dynamic ordinary least squares (weighted DOLS) and weighted fully  
 311 modified ordinary least squares (weighted FMOLS) to re-estimate the three models to further show  
 312 the influences of regressors on CO<sub>2</sub> emission. The DOLS and FMOLS apply parametric and non-  
 313 parametric approach, respectively. Unlike the latter, the former uses lags and leads of the regressors.

314 Consequently, the results obtained from these techniques are reliable as they correct for possible  
 315 endogeneity in explanatory variables, and autocorrelation in the residual term. The weighted FMOLS  
 316 estimator (Kao and Chiang, 2000) is given by Eq. (7) and the weighted DOLS regression (Mark and  
 317 Sul, 1999) is given by Eq. (8). In the equations,  $\hat{\beta}$  denotes the long-run estimate,  $C_{it}$  is the regressand  
 318 (carbon emissions),  $Z_{it}$  are the regressors,  $\hat{\lambda}_{12}$  is the serial correlation correction term, and the  
 319 individual long-run variance estimates are  $\hat{w}_{1,2i}$ .

$$320 \quad \hat{\beta}_{FMOLS} = \left( \sum_{i=1}^N \left\{ \sum_{t=1}^T (Z_{it} - \bar{Z}_i)^2 \right\} \right)^{-1} \left( \sum_{i=1}^N \left\{ \sum_{t=1}^T [Z_{it} - \bar{Z}_i] \hat{C}_{it} - \hat{\lambda}_{12i} \right\} \right) \quad (7)$$

321

$$322 \quad \hat{\beta}_{DOLS} = \left( \sum_{i=1}^N \hat{w}_{1,2i}^{-1} \sum_{t=1}^T Z_{it} Z_{it}' \right)^{-1} \left( \sum_{i=1}^N \hat{w}_{1,2i}^{-1} \sum_{t=1}^T Z_{it} C_{it}' \right) \quad (8)$$

323

#### 324 4. Findings and discussions

325 This study executes CD-test (Pesaran, 2004) to confirm the existence of CSD in individual panel  
 326 dataset (i.e., to test  $H_0$ : cross-sectional independence exists). Table 2 presents the outcomes of the  
 327 test and suggests rejecting the null hypothesis at the 1% significance level.

328 **Table 2: Results of cross-sectional independence**

	lnC	lnB	lnF	lnTRO	lnP	lnG	lnGsq
CD-test	5.105***	43.375***	39.395***	6.166***	28.501***	13.957***	14.184***
Prob. value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

329 Note: Prob. denotes probability.

330

331 As the results suggest that the variables in the panel have CSD, appropriate methods of estimation  
 332 should be employed. In this regard, we apply bootstrap to our estimations to address this issue. More  
 333 so, we employ weighted DOLS and the weighted FMOLS methods. These second-generation  
 334 estimators can deal with possible autocorrelation and endogeneity problems that may occur (Dogan  
 335 and Seker, 2016; Li et al., 2011).

336 Next, the study tests the integration properties of variables by implementing CADF and CIPS  
 337 panel unit root test. Both tests are appropriate as they yield better results in the existence of CSD  
 338 (Dogan and Inglesi-Lotz 2017; Pesaran, 2003, 2007). The test is conducted using a model that  
 339 includes a time trend and the one without time trend. The outcomes provided in Table 3 indicate that  
 340 all series are stationary, indicating that they are I(1). With these outcomes, the analyzed series satisfy  
 341 the required conditions and thus we test the long-run relationships of the series.

342  
 343 **Table 3: CADF and CIPS panel unit root test results**

Variable	CADF test				CIPS test			
	Without trend		With trend		Without trend		With trend	
	(Level)	( $\Delta$ )	(Level)	( $\Delta$ )	(Level)	( $\Delta$ )	(Level)	( $\Delta$ )
lnC	-1.409	-3.231***	-2.447	-3.250***	-1.433	-5.815***	-2.927***	-5.899***
lnB	-2.007	-3.748***	-2.364	-3.871***	-2.875***	-5.863***	-3.089***	-6.038***
lnF	-1.919	-3.358***	-2.041	-3.389***	-2.638***	-5.549***	-2.812***	-5.653***
lnTRO	-2.011	-3.659***	-1.985	-3.901***	-1.833	-5.251***	-1.874	-5.364***
lnP	-1.601	-3.598***	-1.651	-3.743***	-1.631	-3.073***	-1.669	-3.352***
lnG	-1.371	-2.621***	-1.974	-3.326***	-1.393	-4.028***	-2.244	-4.069***
lnGsq	-1.434	-2.633***	-2.037	-3.308***	-1.455	-4.355***	-2.229	-4.422***

344 Note: Significant statistic with p-value  $\leq 0.01$  is indicated by \*\*\*.

### 345 4.3. Cointegration test results

346 The study conducts Kao test (Kao, 1999) to determine the cointegration of the series. Table 4  
 347 displays the output of the tests for the three models, which fails to support the null hypothesis.  
 348 Hence, we conclude that a cointegrating relation exists among carbon emissions, biomass energy use,  
 349 fossil fuel use, trade, population, GDP per capita and its quadratic term.

350

351  
 352 **Table 4: Kao-Cointegration test results**

	Model 1		Model 2		Model 3	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
Augmented Dickey-Fuller	-7.193***	0.000	-7.320***	0.000	-7.374***	0.000

353 Note: Significant statistic with p-value  $\leq 0.01$  is indicated by \*\*\*.

354

355 In addition, we implement the Pedroni test (Pedroni, 1999, 2004) as it is appropriate for  
 356 heterogeneous panels and the outputs of the tests are shown in Table 5. The outputs, based on the  
 357 common and individual AR parameter options, suggest that the test statistics do not corroborate the  
 358 null hypothesis of no long-run relation. Hence, we conclude that there exists cointegrating relation  
 359 between carbon emissions and the regressors in all panels for the three models.

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**Table 5: Pedroni test for cointegration**

	Model 1		Model 2		Model 3	
	Stat.	Weighted Stat.	Stat.	Weighted Stat.	Stat.	Weighted Stat.
Common AR parameter (within-dimension tests)						
Panel v-Stat.	-2.144	-1.951	-2.052	-1.935	-2.950	-2.643
Panel rho-Stat.	-1.634*	-2.494***	-0.594	-1.083	-0.251	-1.010
Panel PP-Stat.	-4.406***	-5.633***	-4.894***	-5.309***	-3.473***	-4.638***
Panel ADF-Stat.	-0.981	-3.698***	-5.973***	-5.770***	0.563	-2.489***
Individual AR parameter (between-dimension tests)						
Group rho-Stat.	-0.553		0.493		0.901	
Group PP-Stat.	-4.682***		-4.749***		-3.971***	
Group ADF-Stat.	-3.854***		-5.061***		-4.447***	

362 Note: Stat. denotes Statistic. Significant statistics with p-value  $\leq 0.01$  and  $\leq 0.1$  are indicated by \*\*\* and \*, respectively.

363  
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365 The Kao, and Pedroni tests of cointegrating relation employed are regarded as first-generation  
366 tests due to their assumption that cross-sectional independence exists. This assumption might bias the  
367 cointegration test results. Thus, we conduct a second-generation test of cointegrating relation among  
368 the series by applying the Westerlund (2007) bootstrap ECM panel cointegration tests to verify  
369 whether the first-generation tests of cointegration are valid. The bootstrap ECM panel cointegration  
370 tests address the concerns over CSD as well as the issue of heterogeneity across the panel while  
371 determining the cointegrating relation between the series. For the three models, the outputs of the  
372 tests presented in Table 6 confirm that there exists cointegrating relation between the variables in  
373 support of the alternative hypothesis.

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**Table 6. Westerlund bootstrap ECM panel cointegration tests**

	Model 1			Model 2			Model 3		
	Value	Z-value	Robust p-value	Value	Z-value	Robust p-value	Value	Z-value	Robust p-value
Gt	-3.332***	-3.713	0.000	-3.590***	-3.959	0.003	-3.591***	-3.965	0.000
Ga	-13.830***	-0.456	0.000	-14.204***	0.374	0.005	-13.766***	0.587	0.005
Pt	-12.524**	-3.628	0.028	-14.671***	-4.791	0.003	-13.094**	-3.333	0.033
Pa	-11.482*	-1.148	0.080	-12.728*	-0.678	0.073	-11.156	0.076	0.185

378 Note: Significant statistics with p-value  $\leq 0.01$ ,  $\leq 0.05$ , and  $\leq 0.1$  are indicated by \*\*\*, \*\*, and \*, respectively. Bootstrap achieved  
379 using 400 replications for all the models.

380

381 *4.5. Results of cointegration estimates*

382 We estimate the long run influences of regressors on CO<sub>2</sub> emissions by applying PMG, MG and DFE  
383 estimators. These estimators provide solutions to heterogeneity bias. The MG estimator is  
384 appropriate for models with heterogeneous influences (Pesaran and Smith, 1995) whereas PMG and

385 DFE estimators are suitable for models with homogeneous influences (Pesaran and Shin, 1999).  
 386 Besides, the panel ARDL models are suitable for use even if the series possess mixed order of  
 387 integration, such as I(1), and I(0) (Pesaran and Shin, 1999). Table 7 presents the results of  
 388 estimations in which the Hausman test suggests that the long-run slope coefficients are indeed  
 389 homogeneous and consequently PMG is an efficient estimator compared to MG. Thus, we focus on  
 390 interpreting the outputs from PMG and DFE estimators. Also, the coefficients of adjustment as  
 391 indicated by error correction terms (ECT) are found to be negatively significant at 1% for all the  
 392 estimators in all the models.

393 The outcomes from PMG estimator show that all the regressors play crucial role in affecting the  
 394 African environments in all the models. Specifically, we find that GDP per capita (lnG) has positive  
 395 relation with CO<sub>2</sub> emissions. This relationship is significant at 1% in all the models and suggests that  
 396 a rise in income of African countries increases CO<sub>2</sub> emissions, thereby worsening the quality of  
 397 African countries' environment. However, the initial positive effect of income on emissions  
 398 continues up to a point where it turns negative as indicated by the significant negative coefficient of  
 399 quadratic income (lnGsq). This suggests an inverted U-shaped relation of income with CO<sub>2</sub> emission  
 400 in African society where biomass energy is in use. The inverted U-shaped association observed for  
 401 African countries can be linked to structural change in income and an improved technology, which  
 402 lead to early worsening of environment. But the subsequent reduction in environmental degradation  
 403 along with increasing income can be ascribed to various environmental control measures and policies  
 404 applied to lessen pollution in order to meet societal demand for better environment. Related studies  
 405 with results supporting EKC in a model including biomass energy use include Dogan and Inglesi-  
 406 Lotz (2017), Shahbaz et al. (2018), and Danish and Wang (2019).

407  
 408

**Table 7. Estimated coefficients from long-run estimators**

Variable	Model 1			Model 2			Model 3		
	Coefficients			Coefficients			Coefficients		
	PMG	MG	DFE	PMG	MG	DFE	PMG	MG	DFE
lnG	4.411***	3.995	2.351***	4.662***	10.895	2.928***	4.404***	2.542	1.888***
lnGsq	-0.265***	-0.193	-0.112**	-0.279***	-0.697	-0.144***	-0.261***	0.036	-0.079
lnF	0.490***	0.564**	0.471***	0.478***	0.522***	0.445***	0.450***	0.596***	0.490***

lnB	-0.169***	-0.534*	-0.451***	-0.154**	-0.371	-0.379***	-0.113**	-0.611**	-0.442***
lnTRO	-	-	-	-0.063**	-0.097	-0.174***	-	-	-
lnP	-	-	-	-	-	-	0.044*	-1.464	0.117**
ECT	-0.365***	-0.611***	-0.382***	-0.381***	-0.684***	-0.393***	-0.427***	-0.712***	-0.394***
Hausman test	0.375			0.904			0.635		

Notes: Significant statistics with p-value  $\leq 0.01$ ,  $\leq 0.05$ , and  $\leq 0.1$  are indicated by \*\*\*, \*\*, and \*, respectively.

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411 We also find that fossil fuel energy use (lnF) affects CO<sub>2</sub> emissions positively, and the effect is  
412 significant at 1%. This implies that a 10% increase in fossil fuel energy use results in around 4.9%  
413 increase in CO<sub>2</sub> emissions in the model without trade and population as regressors. The effect of  
414 fossil fuel slightly decreases to 4.8% when only trade is included in model 2, and to 4.5% when only  
415 population is included in model 3. The result is as expected since fossil fuel energy constitutes most  
416 important source of CO<sub>2</sub> emissions (Bilgili, 2012; Katircioglu, 2015).

417 Due to the need to meet societal demands for better environmental quality and because African  
418 countries are endowed with alternative energy source such as biomass, which has less carbon  
419 emissions, we examine the potential of biomass energy use to lessen the deterioration of  
420 environmental quality. Interestingly, results from the PMG estimator indicate that biomass energy  
421 use (lnB) has a dampening effect on CO<sub>2</sub> emissions in those countries. Precisely, the influence of  
422 biomass energy use on CO<sub>2</sub> emissions is negatively significant in the three models. That is, as  
423 biomass energy usage increases by 10% CO<sub>2</sub> emissions reduces by around 1.7%, 1.5%. and 1.1% in  
424 the three models respectively. As found in this study, the utilization of biomass energy with its  
425 dampening effect on CO<sub>2</sub> emissions lends support to similar results found by Bilgili (2012) for USA,  
426 Katircioglu (2015) for Turkey, Dogan and Inglesi-Lotz (2017) for 22 biomass consuming countries,  
427 Adewuyi and Awodumi (2017) for Burkina Faso, Gambia, and Mali, Danish and Wang (2019) for  
428 BRICS countries, Sarkodie et al. (2019) for Australia, Danish and Ulucak (2020) for China.

429 While fossil fuel energy use is found to increase CO<sub>2</sub> emissions, biomass energy use decreases the  
430 emissions to support the current global switch to a decarbonized economy. This means that African  
431 society can quickly record progress in achieving green economy if substantial preference is given to  
432 biomass energy use. Undoubtedly, this is possible because the countries are very rich in biomass

433 energy sources varying from forestry and agricultural remains, wood made from agro-industrial  
 434 plantations to non-wood generated from plant stems, and crop remains. Given these resources,  
 435 biomass as source of renewable energy could serve as substitute to fossil fuel, a non-renewable  
 436 energy source if the endowed biomass resources are employed efficiently.

437 From the results of model 2 in Table 7, trade openness exerts significant negative impact on  
 438 carbon emissions, suggesting that an increase in trade openness by 10% leads carbon emissions to  
 439 decrease by 0.6%. This result corroborates that of Awad (2019), Dogan, and Seker (2016), Jebli et al.  
 440 (2016), and Al-Mulali et al. (2015) but contradicts that of Danish and Wang (2019). The  
 441 improvement in the quality of environment resulting from increased trade may be due to technique  
 442 effect from the import and use of technologies which are friendly to environment. It may also be due  
 443 to composition effect exerted by increased trade in which the sectors producing goods a country has  
 444 comparative advantage are not energy intensive and consequently, a reduction in pollution.

445 It is noted that population is among the important factors a path-breaking approach will include in  
 446 an environmental model (Fan et al. 2006). The result of including population in model 3 shows  
 447 significant positive coefficient, which suggests that a 10% growth in population results in a 0.4%  
 448 increase in CO<sub>2</sub> emissions. This supports the findings of Fan et al. (2006), Hashmi and Alam, (2019)  
 449 and Rauf et al. (2018) in which population is found to contribute to increased carbon emissions.

450 Turning to the outputs obtained from DFE estimator, Table 7 show the significant impacts of all  
 451 the regressors, except the quadratic income in model 3, on CO<sub>2</sub> emissions with expected signs. In this  
 452 respect, the DFE results are somewhat similar to those reported for PMG estimator.

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**Table 8. Robustness test results from Weighted FMOLS and DOLS**

Variable	Model 1		Model 2		Model 3	
	Coefficients		Coefficients		Coefficients	
	FMOLS	DOLS	FMOLS	DOLS	FMOLS	DOLS
lnG	2.371***	3.642***	2.573***	3.787***	1.912***	3.117***
lnGsq	-0.137***	-0.195***	-0.143***	-0.198***	-0.091***	-0.156***
lnF	0.414***	0.412***	0.406***	0.395***	0.475***	0.429***
lnB	-0.446***	-0.286***	-0.419***	-0.268***	-0.461***	-0.294***
lnTRO	-	-	-0.063***	-0.120***	-	-
lnP	-	-	-	-	0.117***	0.179***
R <sup>2</sup>	0.971	0.987	0.973	0.991	0.976	0.992

455 Notes: Significant statistic with p-value  $\leq 0.01$  is indicated by \*\*\*.

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458       Furthermore, we employ second-generation estimation methods like weighted FMOLS, and  
459 weighted DOLS to estimate the same model. These estimators also address possible autocorrelation  
460 and endogeneity problems in the error terms and regressors, respectively. This enables to obtain  
461 robust and reliable estimates of parameters. The results of using weighted FMOLS, and weighted  
462 DOLS are presented in Table 8. The outputs obtained from these estimators indicate that all the signs  
463 of regressors are as expected and they are significant at 1% level thereby supporting the outputs  
464 obtained from PMG and DFE estimators in Table 7. This implies that the long-run estimates  
465 reported for panel ARDL estimators are valid and reliable to make inferences.

466

## 467 **5. Concluding remarks and policy implications**

468 This paper investigates the influences of biomass energy use, fossil fuel, income, trade, and  
469 population growth on CO<sub>2</sub> emission and tests whether there exists EKC in African countries. To  
470 achieve the estimates of the parameters, the study employs PMG, MG, and DFE estimators which  
471 resolve the issue of heterogeneity bias. In addition, we employ weighted FMOLS, and weighted  
472 DOLS to validate the robustness of PMG outputs. The results obtained from each of these estimators  
473 complement one another and both suggest that the relation of population growth and fossil fuel use  
474 with CO<sub>2</sub> emission is positively significant. Conversely, we find that trade openness and biomass  
475 energy use exert significant negative impact on carbon emission. That is, increased trade and  
476 biomass energy consumption have a dampening effect on emissions. More so, these results validate  
477 EKC hypothesis for those African countries. Based on various econometric methods employed in  
478 which the verdict of one approach confirms the verdict of other in the same category, one can  
479 conclude that the reported findings are robust, consistent, and plausible to make inferences.

480       The finding of this study suggests that the effect of population increase harms the African  
481 environment. This implies that population reduction is imperative to lessen carbon emissions in those  
482 countries and the optimal strategy to achieve this is to resort to population growth control. However,

483 opening trade is found to improve the quality of environment in African countries by reducing the  
484 demand for energy use. This is in the right direction and policy makers should ensure consistency in  
485 the policies and regulations guiding the opening trade in those countries.

486 Furthermore, our findings indicate the use of energy sourced from biomass helped to mitigate  
487 emissions in African countries. The results will be useful to motivate the non-users of biomass to  
488 appreciate its dampening effect on emissions. Thus, it is recommended that African countries  
489 encourage the consumption of biomass energy by substituting it for fossil fuel energy since the  
490 countries are endowed with various sources of biomass. To ensure this, the policy making authorities  
491 need to raise more awareness about the benefits of shifting to the use of biomass energy. In addition,  
492 they can make national policies that encourage increase share of biomass in the national energy mix  
493 as this will to a large extent minimize the CO<sub>2</sub> in the air and prevent climate change.

494 Naturally, the panel of African countries is blessed with forest resources from which biomass  
495 energy is majorly generated. Forests play a bigger role in reducing emissions as they currently  
496 remove around 25 percent of CO<sub>2</sub> (National Geographic, 2018). Hence, national policy makers  
497 should formulate a policy that encourages reforestation and improvement of forest management to  
498 ensure the achievement of SDG 15. The implementation of this policy could help to remove from the  
499 air sizable percentage of CO<sub>2</sub> needed for reduction by the year 2030. Also, it is essential to protect  
500 and increase tropical forests due to their crucial roles among which is the cooling of the air. Thus,  
501 appropriate policy which ensures protection of existing forests will be desirable to prevent dangerous  
502 climate change.

### 503 **Declarations**

#### 504 **\*Author Contributions**

505 *All the authors have significantly contributed to carry out this research. Dr Raji Jimoh collected*  
506 *the data, performed econometric analysis, and wrote the result and discussion section. Likewise, Dr.*  
507 *Rana Muhammad Adeel-Farooq completed the Introduction and literature review sections.*

508 *Similarly, Dr. Ghulam Muhammad Qamri wrote the conclusion, done data analysis and reviewed the*  
509 *entire manuscript.*

510 **\*Funding**

511 *The authors declare that no funds, grants or other financial support were received during the*  
512 *preparation of the manuscript.*

513 **\*Competing Interests**

514 *The authors have no financial or non-financial interests to disclose.*

515 **Consent to Participate**

516 Not Applicable

517 **\*Ethical Approval**

518 *All the ethical codes are followed while conducting this research. This research has not been*  
519 *submitted to any other journal except this journal. All the data employed in this research is obtained*  
520 *through reliable sources and true. The analysis has been done in a fair manner.*

521 **\*Consent to Publish**

522 *The publisher hereby is given full consent to publish this research if accepted.*

523 **\*Availability of data and materials**

524 *Data and all the other materials will be shared if required.*

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